CHAPTER 4 DISCUSSION

There are several advantages to using task-based assessment to determine magnetic field exposures. Job title based assessment is the common approach. A worker's job title, however, does not necessarily indicate the magnetic field exposure tasks a worker performs. Task-based assessment is more efficient in that there are fewer tasks required to cover a population than job titles. It is easier to obtain information about what is performed in a task versus a job because a job title can be more variable. Tasks often are the same across jobs and industries, as we found in reviewing the California Occupational Guides. The results can prove to be useful as feedback to a worker if they are able to associate certain tasks with high or low exposure. Task assessment should be simpler and easier to perform than job title assessment, which has traditionally been done.

The list of common tasks we derived is sufficient to cover a broad range of the population, but it probably can't cover all the MF-relevant tasks found in all jobs. The approach used here is to assume that some missing time will fall into the "other" or miscellaneous category and be captured. However, for this to succeed, the questionnaire must at least capture the major activities that relate to MF exposure. We have developed the task questionnaire based on general population data and tested it in a utility worker population with known MF exposure. It is possible that this questionnaire may not capture MF related tasks if applied in a broader range of industries.

The task list can be adapted to other industries by expanding certain categories. For example, our general task category, *electrical utility work and wiring*, was expanded into 4 task categories for the CSU population: *three phase linework*, *single phase linework*, *nonenergized linework*, and *substation*. Without these specific categories, we would have grouped exposure data together that really should have been kept separate. We could have lost valuable information about the tasks performed by these workers. In a different worker population where little of this type of work is done, it may be appropriate to say that all workers in the electrical utility work and wiring category do about the same thing. This is not the case for the CSU population as their tasks range from working on unelectrified to highly electrified systems and one would expect their task exposures to be different.

Task-based assessment probably will be most effective when applied within a specific industry. Within a specific industry, there is greater knowledge about what tasks are routinely performed. Additional MF personal monitoring needs to be done in conjunction with collection of time-diary information to fill in the tasks which could not be observed in our population. This is the only way to arrive at reliable estimates of exposure for a given task.

Identifying common tasks posed a problem in that there is a vast difference in white-collar and blue-collar types of jobs. While there may be as wide a variety of tasks in each type of job, blue-collar jobs tend to perform more industrial type tasks that seem to have greater potential for MF exposure. For example, Methner and Bowman found widely varying MF exposures in a larger survey of major U.S. industries based on Standard Industrial Classification (SIC) coding (Methner and Bowman in press, 2000). White-collar jobs may have many administrative tasks that translate to the same type of MF exposure. An example is someone in an office with a computer who does occasional photocopying or faxing.

4.1 SOURCES AND ENVIRONMENT

We explored the idea of incorporating source use into our task model. Sources included things such as appliances and equipment used on the job that may affect a worker's personal exposure. We developed a methodology statement regarding source information we would like to find:

> *To estimate appliance exposure, it will be necessary to estimate intensity, duration, and frequency of exposure. The metric will aim to characterize TWA (mean) exposure to the chest during typical use. Ideally, we would also like to estimate the variability around the mean (SD). There are two possible components to this variability 1) within person variability, and 2) between person variability. Since the purpose of the task analysis tool is to produce estimates of an individual's exposure, it is the former variability estimate we want to obtain. This may be possible to generate by asking for a range of values for duration and frequency of use and applying this to a distribution of values for the intensity of exposure from the appliance*

database. One approach would be to use a Monte Carlo simulation to produce these exposure estimates.

Early in the project effort was devoted to identify available exposure data for various sources. Ideally, we wanted exposure data under typical user conditions. Enertech was able to provide data from a number of their research projects. Five of these studies were specific to California and three were multi-state studies. We grouped the data into about 20 loosely defined categories. In an attempt to link specific sources to specific tasks. If a worker answered “yes”, that he did perform a certain task on a typical workday, the on-line questionnaire could then take the person to a new page of sources related to those tasks and ask them if they used any of those sources on a typical day. We soon found that there are far too many possible sources (several hundred) and some of the same sources can be linked to many different tasks to make this feasible. Therefore, we concluded that meaningful and specific source information could not be attributed to specific tasks. Further, it would not be possible to validate the contribution of those sources to each task without very precise time logs and an extensive “source” questionnaire.

The question of environment remains. MF exposures during a particular task can have three components: time duration, source characteristics (source intensity), and background environment. We explored incorporating environment as a modifier of exposure, so that task estimates could be increased or decreased depending upon the type of environment a worker is in while performing a task. Through this process, we created a list of different types of common work environments:

Table 1. Examples of Common Work Environments

Outdoor with transmission lines nearby (within 100 feet)
Outdoor with distribution lines nearby (within 50 feet)
Outdoor, working in a manhole or vault
Outdoor, no electrical facilities nearby
Residential building
Office building/ hospital
School/ university
Store/ shopping mall
Commercial/ industrial factory/ warehouse
Specialized environments (airplane, ship, etc.)

In some cases, exposure solely due to location of the work being done may override any effect that the task may have. This does not appear to be the case in our population, since task assessment captured most of the exposure information and spots were less predictive than task estimates. However, some literature suggests that environment may play an important role in MF exposure (Kelsh et al. 2000). This above list could be incorporated in a future version of the questionnaire if it was necessary to collect information on environments.

4.2 ACTIVITY LOG

4.2.1 Limitations of Activity Log Format

It became evident after all the UW activity logs were completed that the formatting led to some workers filling in the information shifted by 1 hour. The box on the log that contained "6:00" was meant to cover the time period 06:00 - 06:59AM. Some workers appeared to interpret this box to cover the time period 05:00 - 05:59AM since the "6:00" was situated near the bottom of the box (see Appendix F). In contrast, for the CSU activity logs, the "6:00" was at the top of the box and signified 06:00 - 06:59AM.

It is clear that format and presentation of the activity log can significantly affect the results that will be received. We believe we were able to determine when this error occurred by careful review of the EMDEX time traces. An indication was when the activity log didn't correspond to changes at breaks or lunch periods shown on the time trace. The time log was invaluable in helping to decipher the activity logs. Since time in actual hours and minutes was written down for the time log, as opposed to drawing lines and arrows for the activity log, we treated this data as the gold standard for comparison.

The categories 7 (office/business machine), 14 (electric power tools), 15 (non-electric power tools), and 17 (using telecommunications equipment devices) all presented recording problems. These categories are similar to each other in that the task is defined in terms of some type of equipment being used. In addition, these tasks are usually performed for short periods of time usually on the scale of less than 15 minutes (operation of power tools may tend to be longer in duration). The time resolution of our current activity log is only about 30 minutes so recording of these tasks tends to be error prone. We found that a person would mark out an entire box (an hour time period) or half a box for these tasks even if it occurred for only a brief period. When reviewing their field versus time graph generated by EMCALC, it was evident that these tasks did not last for an entire hour. Therefore, it seemed that workers were only able to indicate that the specific task was done sometime during that hour, but could not designate exactly when it was done. This will likely lead to misclassification of exposure for these tasks and “dilute” the task specific estimates since the tasks were only performed for part of an hour, but we had to extract data for the whole hour. Depending on what other activity was performed within that hour, we could dilute or inflate the true exposure for the task. These categories need to be redefined. One solution is to redefine these categories and broaden them to include a larger set of activities. Alternatively, the activity log could be refined to give more precise data on task duration or frequency.

4.2.2 Misclassification in Activity Log Reporting

When extracting data from personal exposure EMDEX files, in some cases, it was necessary to second-guess what the worker meant when they recorded their day. We used the times workers indicated that they performed each specific task to know when to extract data. Interpreting a worker’s activity log incorrectly or conversely, taking a worker’s activity log report for face value can introduce gross misclassification. A pertinent example is subject 669 in Table 6. At first, we extracted his personal data based on the times indicated on his activity log. Task means for most categories were much higher than we expected. Examination of his field versus time graphs revealed that his lunch hour was clearly an hour earlier than he had indicated. Careful review of his activity log in comparison to the graphs confirmed this so, it was likely that he had shifted the reporting of all his activities by an hour. We then extracted his personal data shifted by an hour and the means for each task category made much more sense and were more consistent with other task estimates from other subjects. For example, a mean of 0.49 mG for task 31 (meeting) is much more reasonable than a mean of 32 mG. The standard deviations are also reduced, especially for tasks gas/diesel motor vehicle and meeting. Less variation within the task is evidence that a single type of activity was performed during that time period. Not making this type of adjustment, could have been highly influential to the overall task averages when extracting data from subject records. This again highlights an advantage of the robust regression method. This method does not require data extraction but only accurate recording of the amount of time spent on tasks.

Table 2. Subject 669 Data Extracted Two Different Ways to Show Potential Misclassification

Data extracted as indicated on activity log					
Task	**AM**	**SD**	**GM**	**GSD**	**OBS**
2	11.88	32.97	3.211	3.366	474
3	1.35	0.84	1.017	2.701	714
8	10.32	33.07	0.894	7.653	394
31	32.04	66.23	8.801	4.366	57
32	2.48	0.62	2.405	1.300	117
34	6.10	24.23	1.341	4.103	2197
Data extracted shifted by one hour					
Task	**AM**	**SD**	**GM**	**GSD**	**OBS**
2	23.41	48.37	5.645	4.584	474
3	2.10	0.86	1.969	1.439	714
8	0.97	0.84	0.679	2.998	418
31	0.49	0.47	0.330	2.590	57
32	0.57	0.21	0.547	1.278	121
34	6.38	24.74	1.506	3.792	2101

4.3 1000 PERSON STUDY DATA

Prior to the validation study, we attempted to derive task estimates from occupational data found in the 1000 Person study (Zaffanella and Kalton 1998). The inherent problem with this method is that we do not know if the occupations measured were even performing the task on the day they were sampled. Even if they were performing the task, they most likely were not performing it for the entire shift, and they were also likely to be performing other tasks throughout the day. This is the best source of data we could locate for our purposes prior to collecting the validation study data.

Another problem with this data set is that there is no specific exposure information discerning the categories on *electrical utility work and wiring* and *electrical and electronic equipment assembly, testing, and repair*. This has even more relevance to the CSU study population, since it was necessary to break out the electrical utility work and wiring category into four smaller categories. Reasons for including the extra categories are discussed in Methods section 2.3.1. For the validation, there were five total task categories for electrical type work, but all were assigned the same estimated value from the 1000 Person study (1.95 mG). However, the observed data from the validation shows that these five categories are in fact different from each other (see Table 7 below).

Table 3. Hourly Weighted Task Means For Electrical Task Categories

Task Category	Hourly Weighted Task Mean (mG)
Three Phase Linework	9.90
Single Phase Linework	3.38
Nonenergized Linework	2.99
Substation	3.82
Electrical and electronic equipment assembly, testing, and repair	3.53

Assigning a value of 1.95 mG to all five of these categories completely misrepresents the actual exposure values and captures none of the variability inherent between these categories. The fact that the validation was performed using workers employed in an electric utility only partially explains the underestimation. This population of workers also included those who do not work in electrical jobs.

4.4 ADVANTAGES TO A WEB-BASED QUESTIONNAIRE

We developed a preliminary electronic questionnaire, but were unable to test it in the validation study. For the validation study, a written time card format was already being used with the study population. In addition, we needed to obtain real-time task information from workers specific to the shifts where personal and spot measurements data were being collected simultaneously. A written format is better suited to this type of data collection. If an electronic format was used to collect work shift specific information, there would likely be much recall bias due to the delay in recording information. The worker would likely need to wait until the end of his shift to record activities or a computer would need to be available during the shift. In some jobs, this would not be feasible.

Our vision for a web-based questionnaire is that it could be used to collect information on tasks typically performed on the job. The feedback it would provide would then be the worker's estimated exposure for a typical day on the job. This more general exposure estimate would probably be more useful to the average person who might be curious about what potential levels of exposure are present in his or her job. There are also instances where a web-based questionnaire could be useful for a specific set of tasks performed on a specific day. But, as mentioned above, there would need to be some way for the electronic questionnaire to be readily accessible to the worker.

We believe it would be wise to consider furthering this project by creating a web-based questionnaire. This type of questionnaire is readily accessible to workers and the general public. Since it is interactive, it provides results specific to the individual completing the questionnaire. Because it provides rapid feedback, it can help people understand what types of activities contribute to their workplace MF exposure. This type of questionnaire would be easy for researchers to modify as new exposure information became available. The results could be stored in a database or sent back to an email address, which would result in a large data set that could provide useful information about task exposures.

4.5 ROBUST REGRESSION METHOD

The robust regression method of estimating task-specific exposures produced the best agreement in reconstructing personal exposure. This is an optimal model in that it comes closest to fitting the real data and it is able to account for all tasks simultaneously. The benefit of this method is that it only requires a completed time card and the full shift TWA from a worker in order to generate estimated exposures for each task. This saves time in that it is not necessary to enter time periods into EMCALC to extract out task specific data. Data can be added to the growing body of knowledge about task specific exposures more quickly. This method is maximally predictive and requires minimal data extraction.

A drawback is that it may greatly reduce the influence of some tasks. A few tasks in the validation exercise had coefficients that tended toward zero, such as 11 (monitoring in a control room or dispatch center), 15 (non-electric power tools), 16 (installing/maintaining telecommunications), and 17 (using telecommunications equipment devices). These categories have low N's (4 or less) and high uncertainty based on extracted task estimates. When the coefficients exhibit this behavior, it signifies that we need additional data for those specific tasks and additional time spent by subjects performing work that uses these activities. In addition, these categories may have greater misclassification errors and could benefit from refinement of the questionnaire (see section 4.2).

4.6 HOURLY WEIGHTING METHOD

This method of data extraction is simple compared to the Smith weighting method. Both methods produce virtually the same mean, but differ only in their variability estimates. Given this, weighting by hours is a more straightforward method and would be easier to implement for future data analyses.

4.7 SMITH METHOD

The Smith method provides a statistically rigorous treatment of the task information, and produces the smallest variance for each task estimate. In implementing this method, it was necessary to set the minimum nhat equal to 1.5 for the variance formula and degrees of freedom to 1.0 for the confidence interval formula for the tasks of *office/business machine, non-electric power tools*, *installing telecommunications networks*, *welding*, and *freight handling/warehouse*. The formulas would not have worked otherwise, and the consequence is that the confidence intervals for those task estimates are somewhat overestimated. The Smith method treats each task as 1 unit of observation, but assumes the proportion of time is a fixed quantity. The Smith weighting method is similar to the robust regression model in that they each use the fraction of the day as the predictor variable.

4.8 COMPARISON OF METHODS

From Table 4, it is evident that using occupational data from the 1000 person study to estimate tasks is a poor method for recreating actual task values (r^2=0.01). The average deviation from the true value using this method is only 0.25 mG with a standard deviation of 0.78. This is smaller than the average deviation from the hourly weighting and smith weighting methods as well as the no weighting method. However, the magnitude of this difference is only an indication of the average error. The difference is that the deviations are correlated with the true mean for those three categories, while they are essentially random for the 1000 person study method. There is no pattern to the estimates produced by this method.

4.9 SPOT MEASUREMENT DATA

In addition to personal MF exposure data, we were able to collect a limited number of spot readings tied to specific workers and activities. Due to limitations in data collection, it was only possible to obtain spot readings within a few days of the personal measurements and for selected tasks (see section 2.3.2). When possible, spot readings were collected with identifiable sources associated with the task both on and off. Instances where the *on* measurements are higher than the *off* measurements, indicate that the sources used in the task are more influential of exposure than the environment. Conversely, situations when there is no apparent difference between the source *on* and the *off* measurements indicate that the environment is a stronger factor in the worker's overall exposure.

We were unable to collect sufficient spot data to make definitive conclusions, but we do see trends. The average difference between the source-on compared to source-off readings was +0.4 mG for all the spot readings; this difference was marginally significant in a paired t-test ($p = 0.1$, two tail). There also were more instances (65%) where the source-on reading was greater than the background. In cases where the source-on readings were greater, the average increase in the MF measurement was +0.7 mG. In cases where the source-on readings are lower, the average decrease was –0.1 mG, which arguably is near the resolution of the measurements. This limited data seems to support the notion that information on exposure sources is captured by the activity survey and this contributes above the background environment. However, our spot information does not distinguish between sources that require direct operator contact or other devices that are found in the work area, merely that the sources are associated with a task. Therefore we can't distinguish the contribution of "area sources" to the overall exposure within a task. Also, spot measurements aren't precisely tied to the specific tasks or sources recorded at the time of personal measurements, but typically within a subject, *on* spot measurements are higher than the corresponding personal measurements for the same task.

In terms of the comparison of personal exposure data to the spot data, there is a moderate positive correlation between spot and personal measurements overall subjects. Using log transformed data gives a significant correlation of r = 0.34 (n= 52 observations). However this analysis is strongly influenced by data for subject 602, who had very high spot readings. When 602 is omitted from the analysis, the correlation between spot and personal data improves considerably (r = 0.78, n=46, log-log analysis). The relatively good agreement between the spot readings and personal readings indicates that there is internal validity for the spot data compared to task measurements, despite the fact that spot readings may have occurred up to 4 days after the personal samples. This suggests that the task data is relatively stable over this period of time. This data also suggests that it probably is not feasible to apply a separate source list with the activity assessment approach, since the task measurements already include source contributions. Sources aren't the whole picture. It is important to capture both source and environment, and personal measurements do this. In a task-based assessment, these contributions are averaged over a variety of sources and environments into a composite exposure factor.

4.10 CONCLUSIONS

We were successful in creating a list of common tasks that should cover a majority of the working population in California. This task list can be adapted for use to survey MF exposure in a variety of occupational groups or industries, by expanding some of the task categories or removing irrelevant categories. The task questionnaire was completed by all workers in the pilot study, and showed variation in task recording, indicating we were able to capture separate and distinct tasks. Completion of activity logs by the workers resulted in useful information. We demonstrated that it was feasible to have workers record their daily activities in time-questionnaire format while at work, provided that the activity log is in a simple format and has task definitions that are relatively specific to the industry or occupation where it is being used.

We made several *a priori* judgements of what tasks people perform at work, based on standardized job descriptions. MF exposure data was then collected and partitioned according to these task categories. We then tested this task classification by using different methods of calculating task and subject means. These a priori judgements appeared to give fairly good partitioning of the MF exposure, so that accurate exposure estimates could be obtained. The main limitation of the pilot study was the small population we had to work with. Some difficulty was noted in using data extraction based on the time-activity logs, where limited time resolution may have contributed to misclassification of exposures. The robust regression model can help to account for these reporting inaccuracies, because it does not require exact time recording. The robust regression and Smith weighting methods produced similar task means, at least within the uncertainty of our data. In this analysis, we've attempted to bound the uncertainty in the methods for estimating task means and for subject estimates, but without additional data some exposure situations cannot be estimated confidently.

To address these limitations, future research would need access to a larger population that is more cross-sectional in representing multiple industries. Task sampling could be used to increase sampling efficiency, by concentrating measurements on workers doing uncertain tasks so that "holes" in the task information can be filled. Also, additional personal exposure data would need to be collected for the various job tasks that were not observed in our worker population. The activity log can be used as a screening tool to help identify these workers and develop a sampling plan to obtain information from them.

The results of this study demonstrate the feasibility of using a task-based MF assessment, and show that it can provide reasonable exposure predictions compared to the true exposure. In estimating task-specific means using data extracted form time recordings, weighting by hours is the most simple and direct method for creating the task estimates. Other task-specific estimation methods tested here offer some advantages in terms of lower variability or bias, although the overall degree of improvement is relatively small. To estimate a worker's daily exposure, the task-specific exposure values are simply multiplied by the proportion of time a worker spends performing that activity during a day.

A general task list with 32 activities that is representative of many common occupations in California was developed in the course of this work. A prototype electronic questionnaire to apply this task list to screen workers for MF exposure also was developed. This task list was readily applied to a working population and successfully captured activities related to MF exposure. Task-specific exposure estimates were obtained for most of the activities during the pilot study, with 25 tasks (78%) of the total list represented. Some tasks were not observed in the pilot study and some task-specific exposure estimates currently have large uncertainties. Exposure estimates were created for tasks that were not observed in the pilot study from available data using the 1000 person study. However, the validation results indicate that these task estimates may be unreliable. Therefore, it is not possible to reliably estimate MF exposures for all activity sets that could arise from combinations in the general task list. Future effort should be devoted to testing this MF assessment technique across a broader range of industries and to improving uncertain task estimates. Improvement of the electronic questionnaire could help target future assessments in worker populations, and make this assessment tool easily accessible to the general population.